

Comparison and Evaluation of Sensitivity Analysis Methods for Probabilistic Risk Assessments

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Outline

- Why Sensitivity Analysis is Useful
- Identification of Sensitivity Analysis Methods
- Modeling Testbed
- Example Results and Insights
- Comparison
- Recommendations

Key Questions Answered by Sensitivity Analysis

- Sensitivity analysis can answer the following key questions:
 - » What is the impact of changes in input values on model output?
 - » How can variation in output values be apportioned among model inputs?
 - » What are the ranges of inputs associated with best/worst outcomes?
 - » What are the key controllable sources of variability?
 - » What are the critical limits (e.g., emission reduction target for a risk management strategy)?
 - » What are the key contributors to the output uncertainty?

Research Background: Comparison and Evaluation of Sensitivity Analysis Methods for Food Safety Risk Models

- June 2001 workshop to review sensitivity analysis methods and recommend specific criteria for evaluation of methods
- Applied approximately one dozen sensitivity analysis methods to multiple food safety risk assessment models:
 - » *Vibrio Paraheamolyticus*
 - » *Listeria monocytogenes* in Ready-to-Eat foods
 - » *E. coli* O157:H7 in ground beef
- Publication of literature review and “white papers” as a special section of *Risk Analysis* (June 2002)
- March 2003 workshop to review results and propose priorities for development of a guidance document for practitioners
- Report on evaluation of methods (www.ce.ncsu.edu/risk)
- Guidance on use of methods (www.ce.ncsu.edu/risk)

Research Background: Comparison and Evaluation of Sensitivity Analysis Methods for Exposure Models

- Based on results for food safety risk models, identified seven of the most practical or powerful sensitivity analysis
- Evaluated their applicability to exposure models based on case studies with a simplified Stochastic Human Exposure and Dose Simulation (SHEDS) model
- Two draft final reports by Mokhtari and Frey
 - www4.ncsu.edu/~frey/
 - Volume 1: Review of Available Methods for Conducting Sensitivity and Uncertainty Analysis in Probabilistic Models
 - Volume 2: Evaluation and Recommendation of Methodology for Conducting Sensitivity Analysis in Probabilistic Models
- Journal paper:
 - Mokhtari, A., H.C. Frey, and J. Zheng, “Evaluation and recommendation of sensitivity analysis methods for application to Stochastic Human Exposure and Dose Simulation (SHEDS) models,” *Journal of Exposure Science and Environmental Epidemiology*, 16(6):491-506 (Nov 2006)

Application of Sensitivity Analysis Methods to a Probabilistic Environmental Human Exposure Model

- Objectives:
 - » To evaluate selected sensitivity analysis methods based on practical case studies with a complex model
 - » To present and interpret sensitivity analysis results in a probabilistic framework that includes a temporal dimension

Examples of Sensitivity Analysis Methods for Probabilistic Models

- Nominal range sensitivity analysis
- Differential sensitivity analysis
- **Pearson or Spearman correlation coefficients**
- **Sample or Rank regression analysis**
- **Analysis of variance**
- Classification and regression tree
- **Fourier Amplitude Sensitivity Test**
- **Sobol's Method**
- Response Surface
- Mutual Information Index
- Scatter plots
- Conditional sensitivity analysis

Key Characteristics of the SHEDS-Pesticides Model

- Simplified SHEDS model used as a testbed
- Based on the SHEDS-Pesticides model
 - Non-linearity and interactions between inputs
 - Saturation points
 - Different input types (continuous versus categorical)
 - Aggregation and carry-over effects
 - Inputs with different sampling time scales (e.g., monthly versus daily inputs)

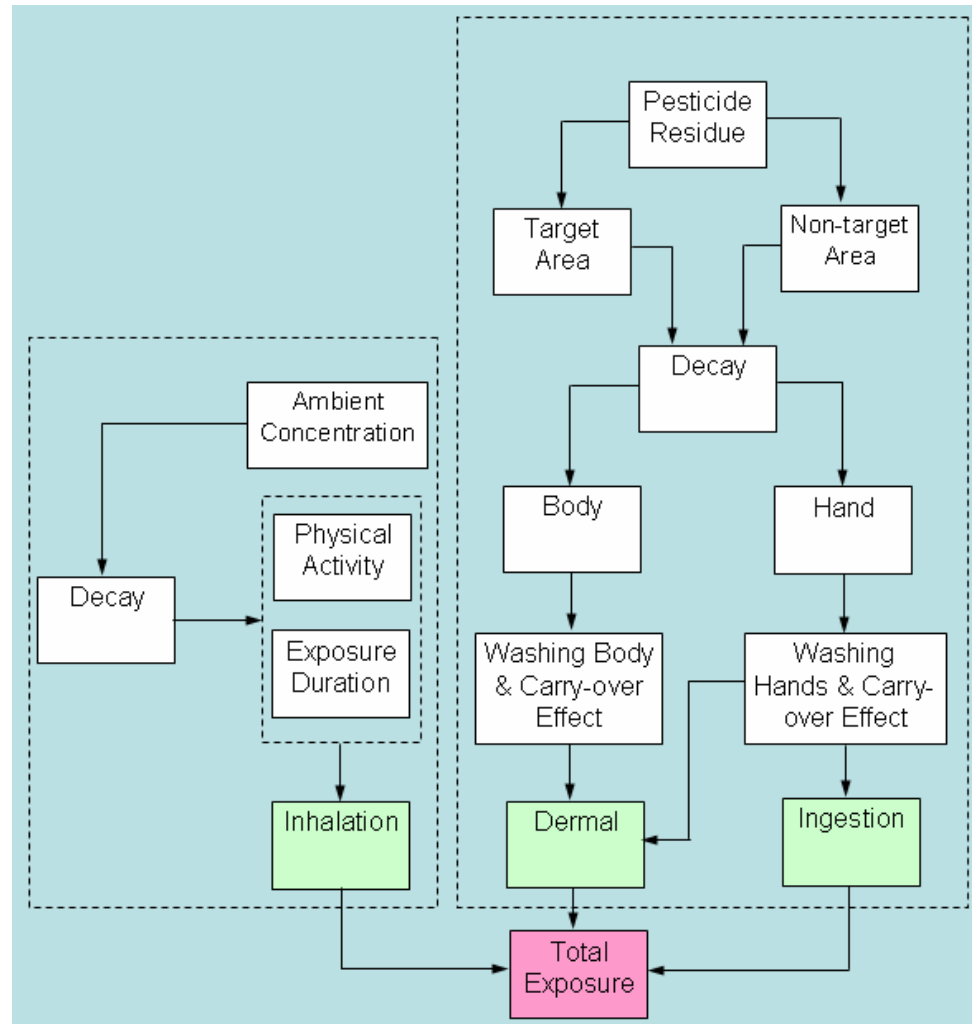
Scenario Assumptions for the Simplified SHEDS-Pesticides Model

- One-stage Monte Carlo simulation
- Inter-individual variability
- Exposure duration of one month
- One application of pesticides at the beginning of the month
- Randomly generated exposure times corresponding to different pathways

Case Study Scenario

- Inter-individual variability in exposures
- Children between 5 and 10
- Total exposure from inhalation, ingestion, and dermal routes
- Three temporal scenarios:
 - Scenario I: Daily total exposure
 - Scenario II: Rate of change of exposure from one day to the next
 - Scenario III: Cumulative Exposure

Schematic Diagram of the Simplified SHEDS-Pesticides Model



Example input Assumptions for the Simplified SHEDS-Pesticides Model: Inhalation Pathway

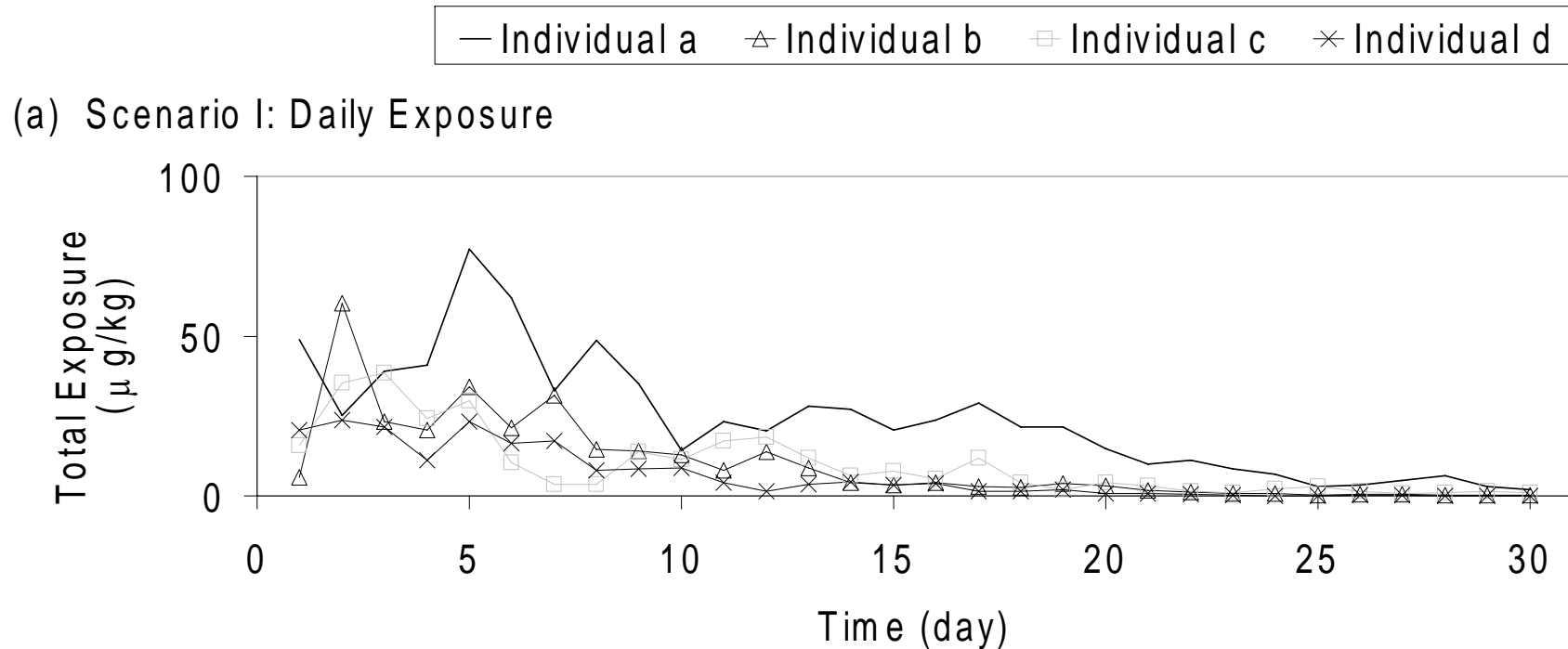
Inputs	Comments	Distribution	Units	Time Scale
C_{air}	Ambient Concentration of Applied Pesticides	Triangular (0.1,1.0,4.0)	$\mu\text{g}/\text{m}^3$	monthly
C_b	Background Air Concentration	Lognormal (6.8×10^{-4} ,1.87)	$\mu\text{g}/\text{m}^3$	monthly
D_{inh}	Inhalation Exposure Duration	Normal(550,140)	min	daily
PAI	Physical Activity Index	Normal(1.75,0.2)	kcal/kg/day	daily
k	Decay Rate for Pesticides Concentration	Tringular(0.05,0.13,0.40)	1/day	monthly
W_B	Body Weight	Lognormal(30,1.3)	kg	monthly

26 probabilistic inputs in total

Model Application

- Each sensitivity analysis method applied to each time step (i.e., day)
- Ranking - comparative order of importance of an input on a given day when sorted according to sensitivity indices
- Rank = “1” for input with the highest sensitivity index

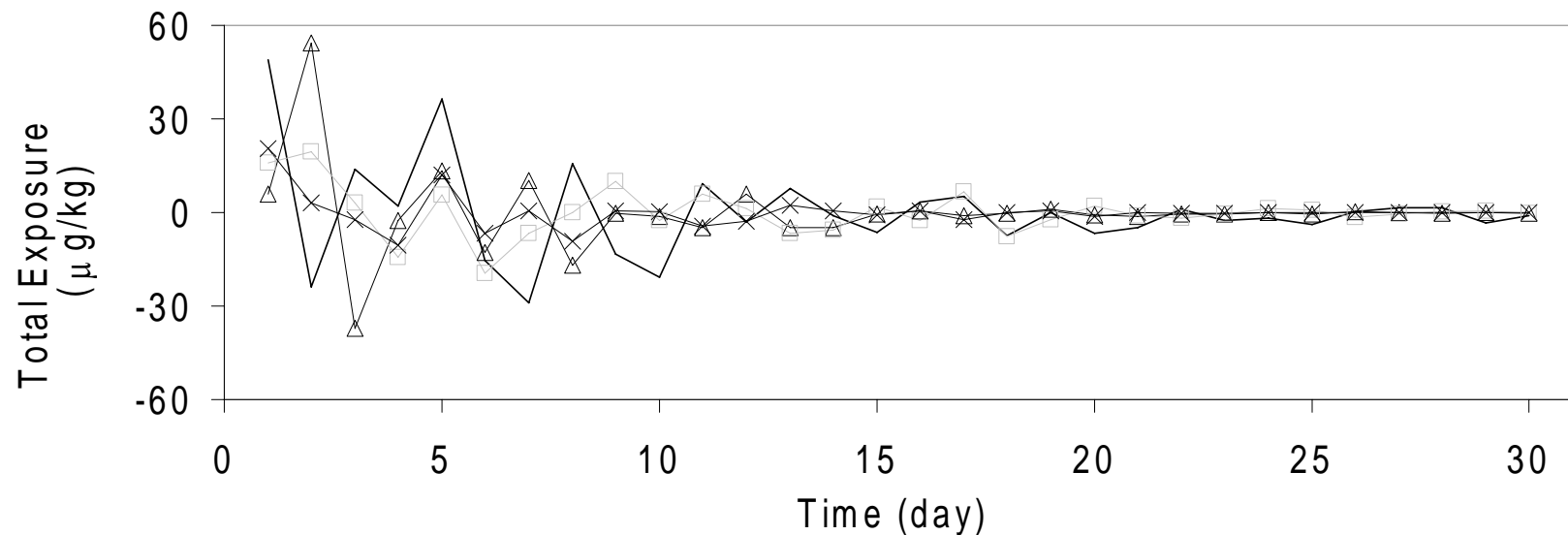
Example Model Output: Daily Exposure for Selected Individuals



Example Model Output: Incremental Change in Daily Exposure for Selected Individuals

— Individual a △ Individual b □ Individual c × Individual d

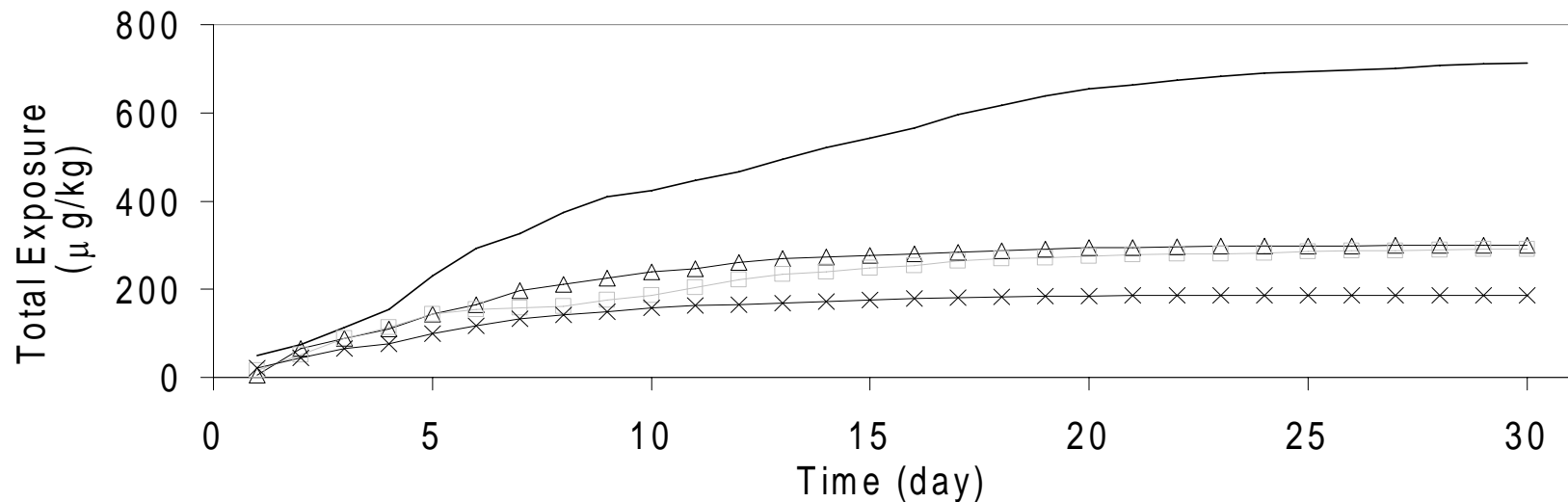
(b) Scenario II: Incremental Change in Daily Exposure



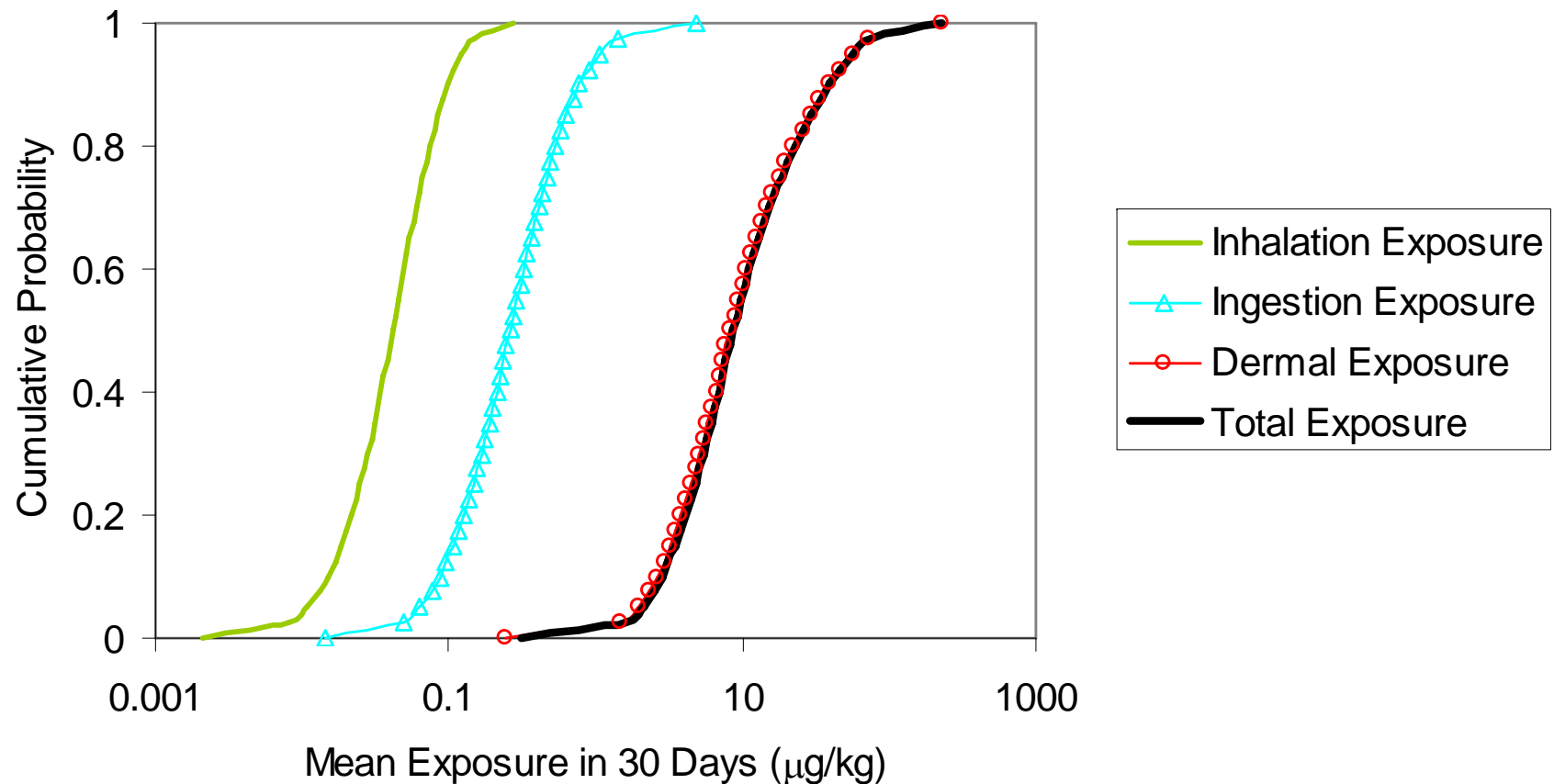
Example Model Output: Cumulative (Temporal) Exposure for Selected Individuals

— Individual a \triangle Individual b \square Individual c \times Individual d

(c) Scenario III: Cumulative Exposure



Example Model Output: Inter-Individual Variability in Exposure Over 30 Days



Pearson and Spearman Correlation Coefficients

- Pearson - sample
- Spearman - rank
- Applicable to results of a Monte Carlo analysis
- Correlation coefficients can range from -1 to +1

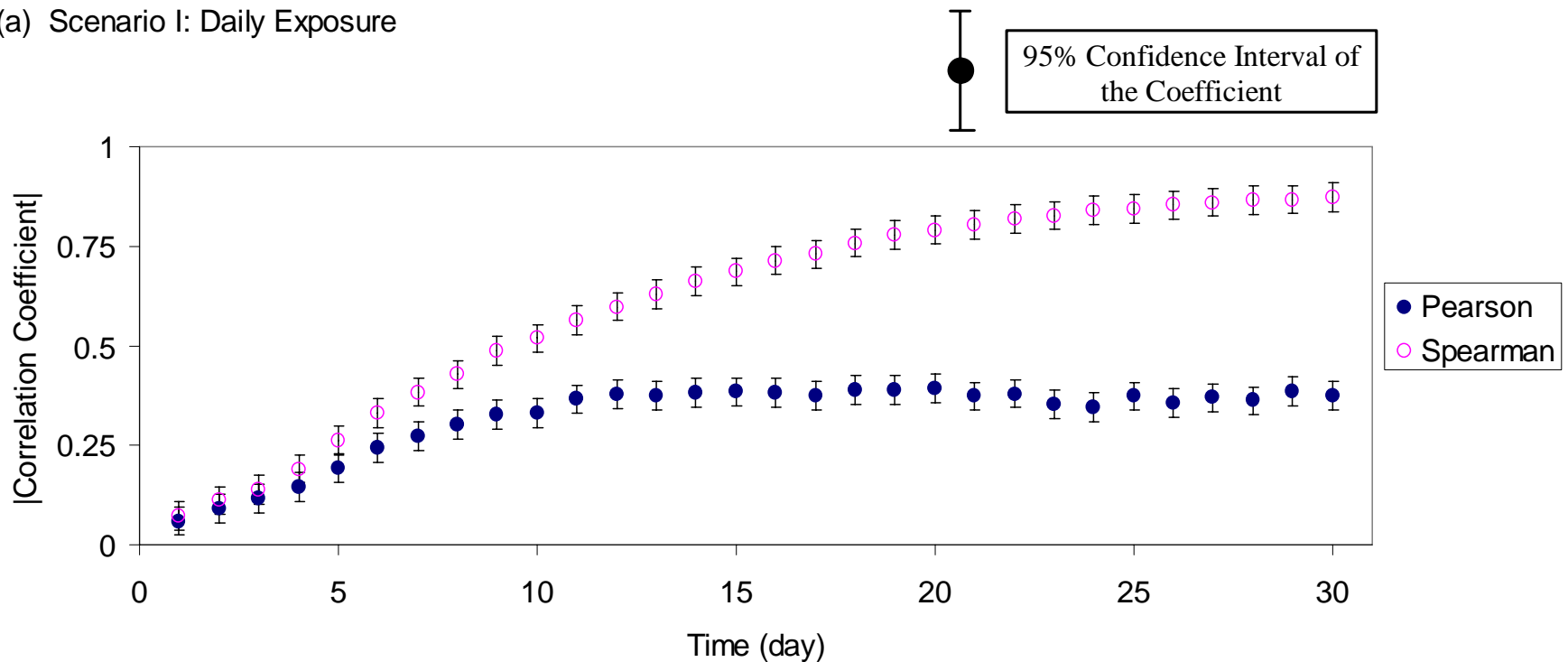
$$r = \frac{\sigma_{XY}}{\sigma_X \times \sigma_Y} = \frac{\sum_{i=1}^n (x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \times \sum_{i=1}^n (y_i - \bar{y})^2}}$$

Pearson (Sample) and Spearman (Rank) Correlation Coefficients (continued)

- Advantages:
 - Relatively easy to compute
 - Can be applied to two-dimensional probabilistic frameworks (correlations for variability, correlations for uncertainty)
 - Readily available in many commercial software packages
- Disadvantages:
 - Pearson correlation - inaccurate for nonlinear models
 - Spearman correlation - inaccurate for non-monotonic models
 - Does not capture interactions among multiple inputs

Example Application of Pearson and Spearman Correlation Coefficients to the Simplified SHEDS Model

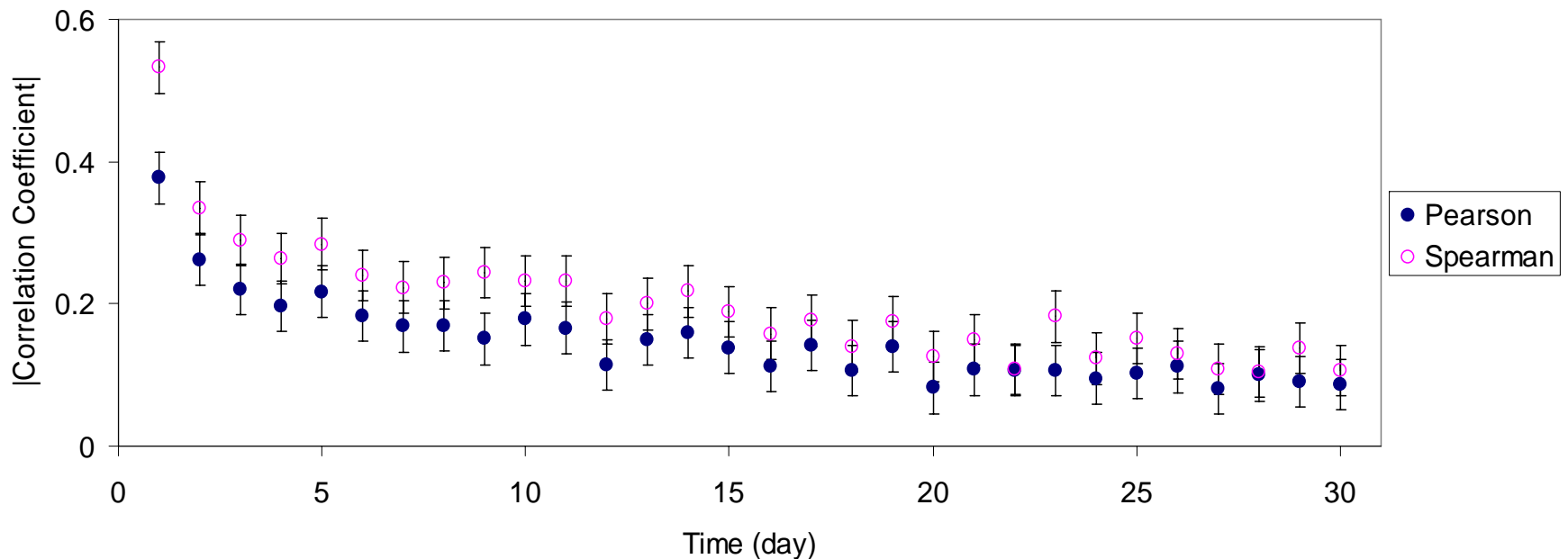
(a) Scenario I: Daily Exposure



Output: Inter-Individual Variability in Daily Exposure
Input: Residue decay rate (monthly)

Example Application of Pearson and Spearman Correlation Coefficients to the Simplified SHEDS Model

(a) Scenario I: Daily Exposure

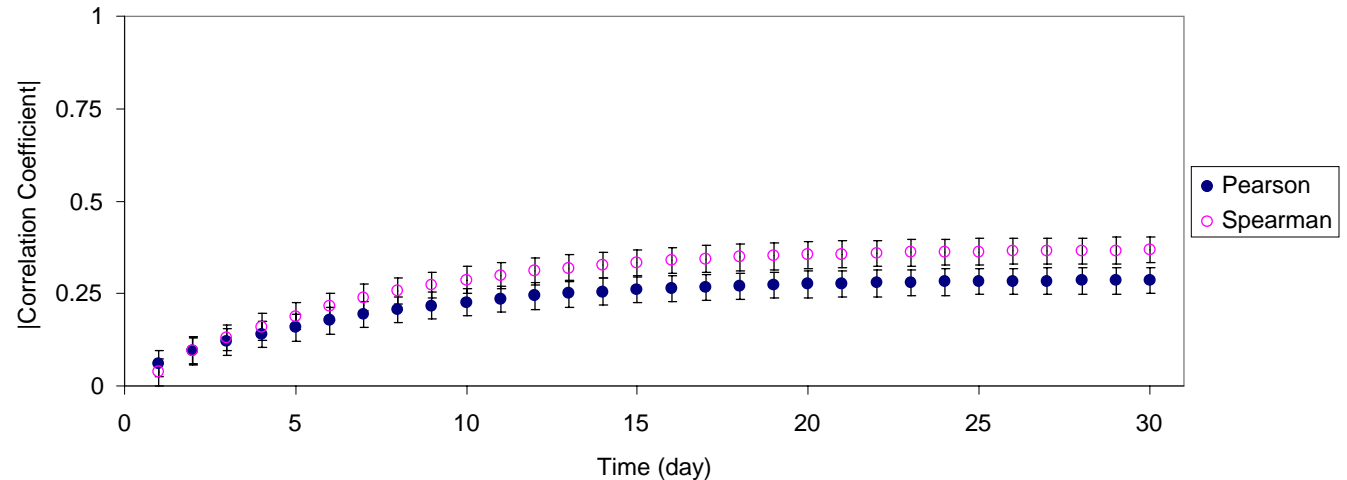


Output: Inter-Individual Variability in Daily Exposure

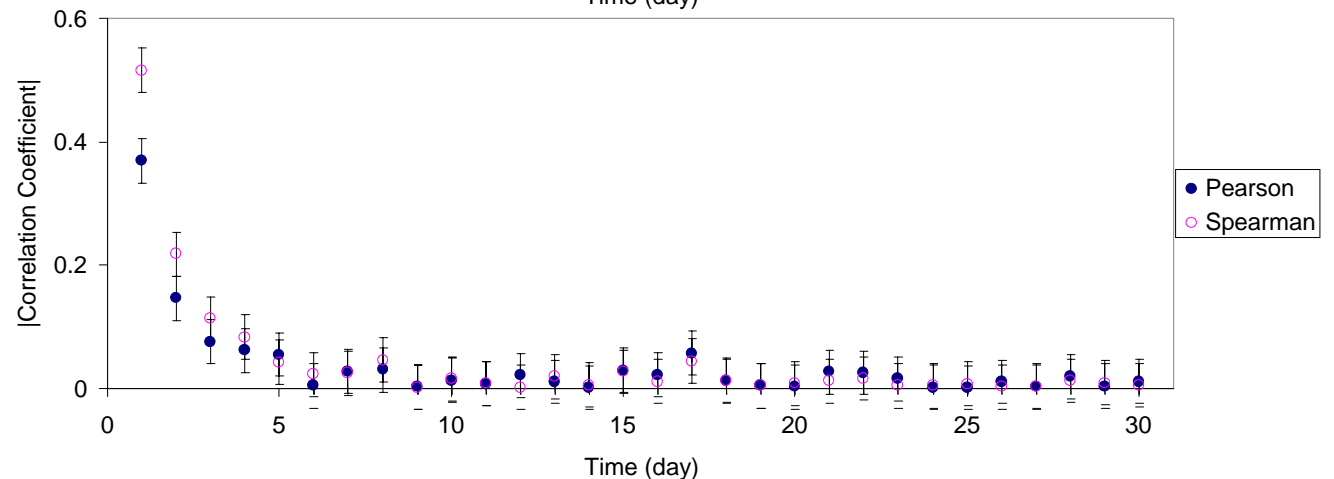
Input: Fraction of Chemicals Available for Transfer (Daily)

Example Application of Pearson and Spearman Correlation Coefficients to the Simplified SHEDS Model

Input: Residue Decay Rate (Monthly)



Input: Fraction of Chemicals Available for Transfer (Daily)



Output: Inter-Individual Variability in Cumulative Exposure

Fourier Amplitude Sensitivity Test (FAST)

- FAST is a variance-based “global sensitivity analysis” method
- FAST can identify the contribution of individual inputs to the expected value of the output variance
- FAST does not assume a specific functional relationship
- FAST can evaluate sensitivities based on varying only one input or all inputs simultaneously
- FAST provides insights regarding *main* and *total effects* of inputs

Definition of Main and Total Effects

- *Main effect* provides insights regarding contribution of each input to the output variance
- *Total effect* of an input is defined as the sum of all effects involving that input, including interaction effects with other inputs
- Example of *total effect* of X_1 for a case with three inputs:

$$ST_{X_1} = S_{X_1} + S_{X_1 \times X_2} + S_{X_1 \times X_3} + S_{X_1 \times X_2 \times X_3}$$

The diagram illustrates the decomposition of the total effect of input X_1 . The equation $ST_{X_1} = S_{X_1} + S_{X_1 \times X_2} + S_{X_1 \times X_3} + S_{X_1 \times X_2 \times X_3}$ is shown. The term S_{X_1} is enclosed in a green circle, and a green box labeled "Main effect of X_1 " has an arrow pointing to it. The remaining terms are grouped within a pink rounded rectangle, and a pink box labeled "Interaction effects involving X_1 " has an arrow pointing to this group.

Transformation Functions

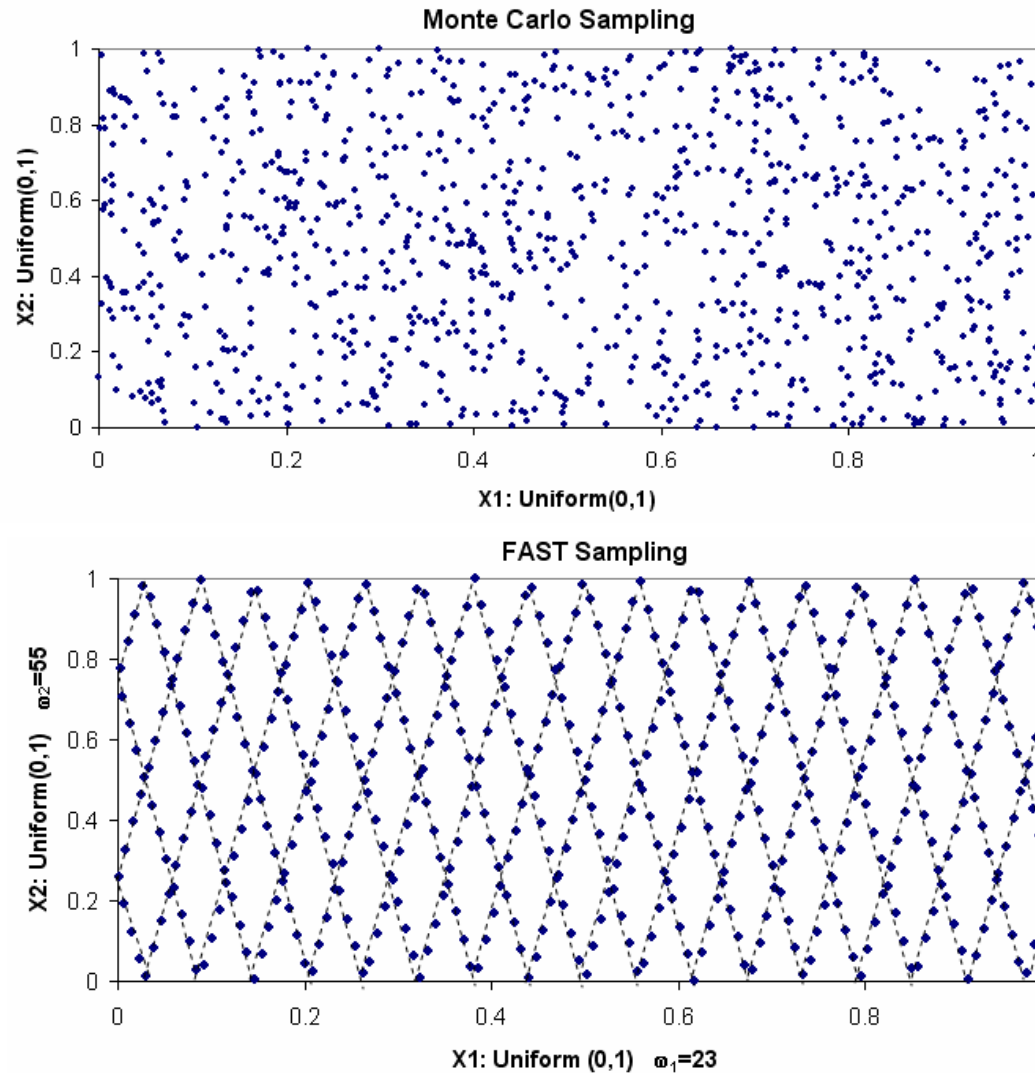
- Application of FAST involves defining a set of transformation functions and frequencies for model inputs:

$$x_i = G_i[\sin(\omega_i s)]$$
$$f(x_1, x_2, \dots, x_n) \rightarrow f(s)$$

$i = 1, 2, \dots, n$; n = number of model inputs
 G_i = Transformation function for i^{th} input
 ω_i = frequency for i^{th} input
 s = scalar variable

- As s varies, all inputs vary simultaneously at rates according to their assigned frequencies
- Frequencies for each input must be distinct and incommensurate

Example of Numerical Samples of Two Uniform Distributions: Monte Carlo vs. FAST



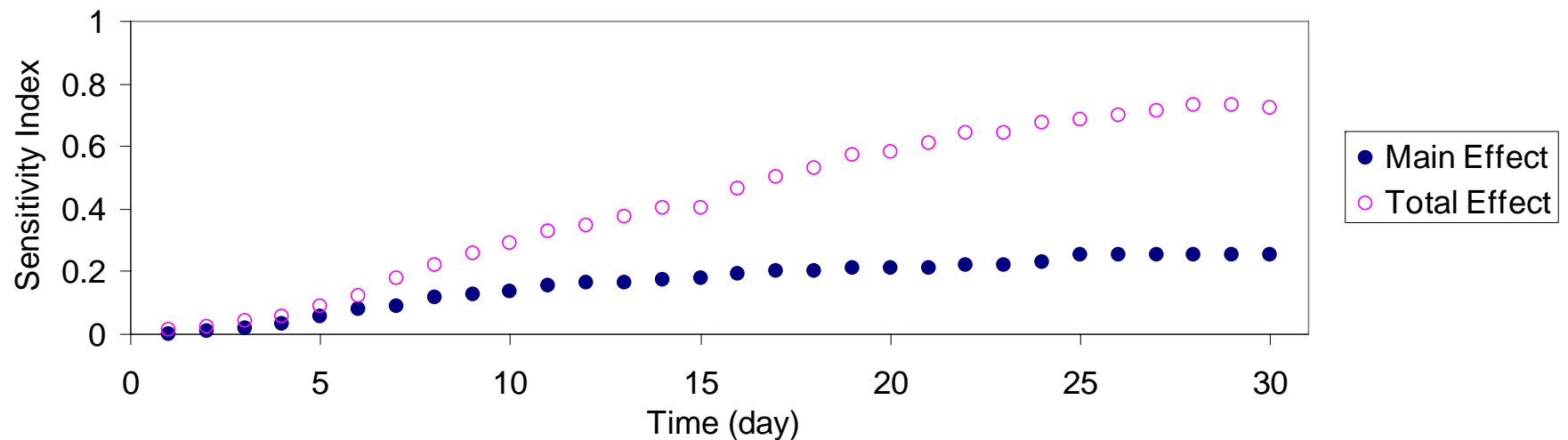
Fourier Amplitude Sensitivity Test (FAST)

(continued)

- Advantages:
 - Model independent
 - Works for **monotonic** and **non-monotonic** models
 - The evaluation of sensitivity estimates for each input is based on just a single set of runs
- Disadvantages:
 - Computationally complex
 - Requires an alternative sampling scheme in place of Monte Carlo
 - The reliability of the FAST method can be poor for discrete inputs
 - Current software tools for FAST are not readily amenable to application to the complex risk assessment models

Example Application of FAST to the Simplified SHEDS Model

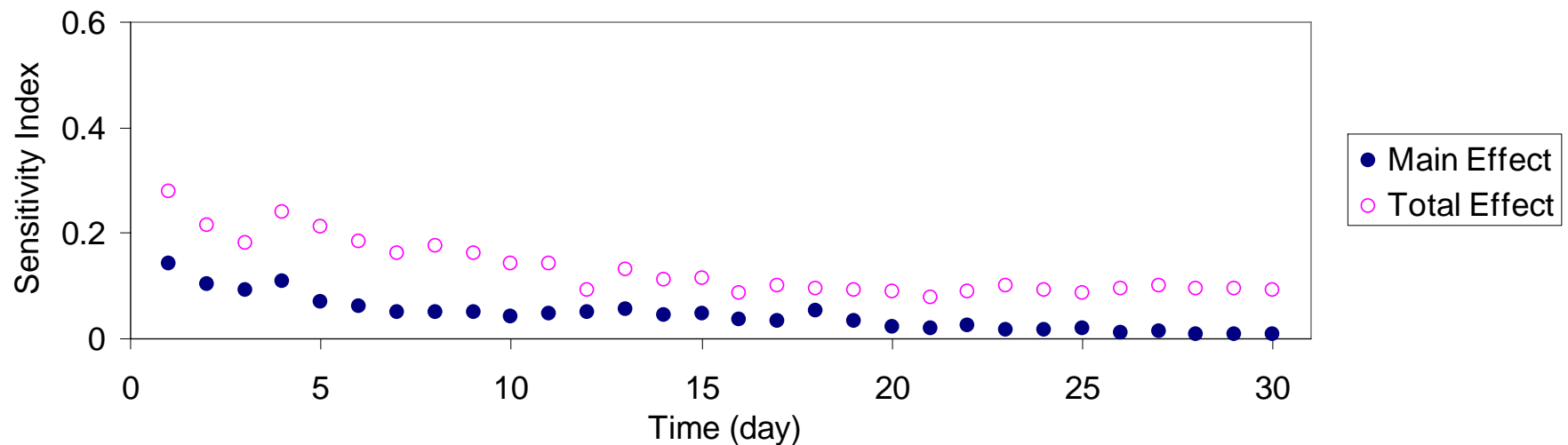
(a) Scenario I: Daily Exposure



Output: Inter-Individual Variability in Daily Exposure
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Example Application of FAST to the Simplified SHEDS Model

(a) Scenario I: Daily Exposure



Output: Inter-Individual Variability in Daily Exposure

Input: Fraction of Chemicals Available for Transfer (Daily)

Sobol's Method

- Variance-based “global sensitivity analysis” method
- Contribution of individual inputs to the expected value of the output variance
- Does not assume a specific functional relationship
- *Main effects*, *total effects*, and any order of *interaction effects* for inputs

Sensitivity Indices Based on the Sobol's Method

- A *Monte Carlo* procedure is used for the estimation of the partial variances, and thus, sensitivity indices
- Example sensitivity indices for *main* and *total effects* of inputs:

Main Effect

$$S_j = \frac{(\hat{U}_j - \hat{E}^2(y))}{\hat{V}(y)}$$

Total Effect

$$ST_j = 1 - \frac{(\hat{U}_{-j} - \hat{E}^2(y))}{\hat{V}(y)}$$

$\hat{E}(y) = \text{Expected Value of } y$

$\hat{V}(y) = \text{Variance of } y$

The Monte Carlo Procedure for Estimation of Sensitivity Indices

- Two input sample matrices M_1 and M_2 are generated (n is the sample size and k is the number of inputs):

$$M_1 = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1k} \\ x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nk} \end{pmatrix} \quad M_2 = \begin{pmatrix} x'_{11} & x'_{12} & \dots & x'_{1k} \\ x'_{21} & x'_{22} & \dots & x'_{2k} \\ \vdots & & \ddots & \vdots \\ x'_{n1} & x'_{n2} & \dots & x'_{nk} \end{pmatrix}$$

- Parameters in the previous equations are estimated as:

$$\hat{E}^2 = \frac{1}{n} \sum_{r=1}^n f(x_{r1}, x_{r2}, \dots, x_{rk}) \times f(x'_{r1}, x'_{r2}, \dots, x'_{rk})$$

$$\hat{U}_j = \frac{1}{n-1} \sum_{r=1}^n f(x_{r1}, x_{r2}, \dots, x_{rk}) \times f(x'_{r1}, x'_{r2}, \dots, x'_{r(j-1)}, x_{rj}, x'_{r(j+1)}, \dots, x'_{rk})$$

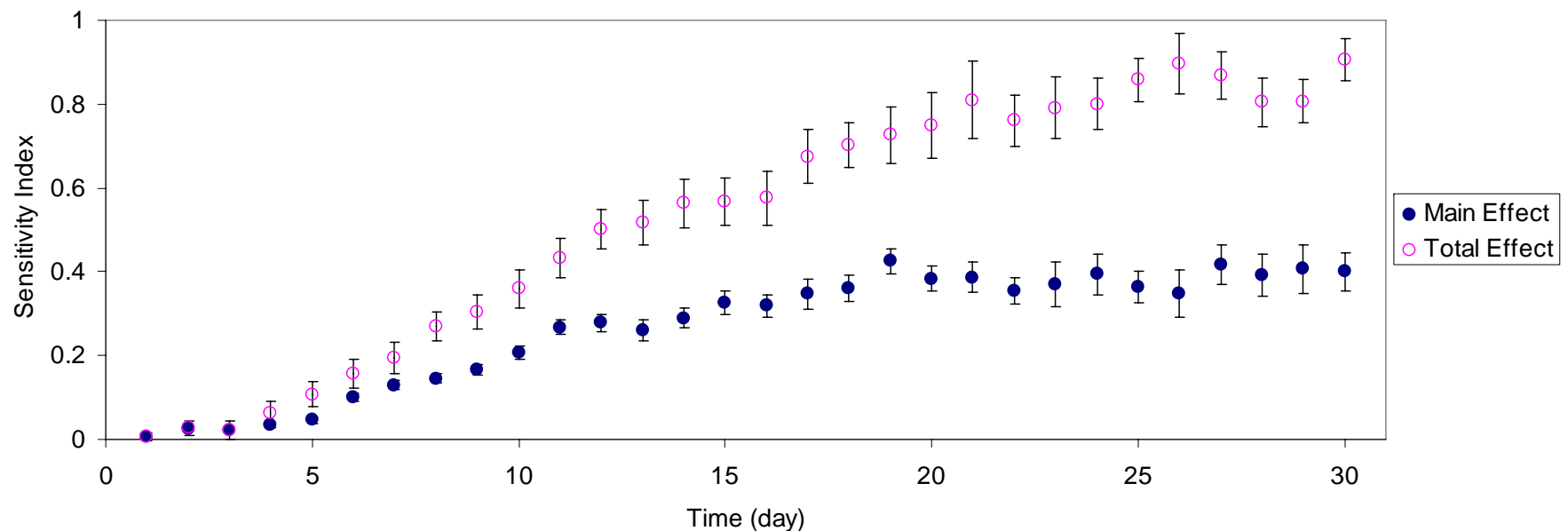
$$\hat{U}_{-j} = \frac{1}{n-1} \sum_{r=1}^n f(x_{r1}, x_{r2}, \dots, x_{rk}) \times f(x_{r1}, x_{r2}, \dots, x_{r(j-1)}, x'_{rj}, x_{r(j+1)}, \dots, x_{rk})$$

Sobol's Method (continued)

- Advantages:
 - Sobol's method can cope with both nonlinear and non-monotonic models
 - Sobol's method can be applied to categorical inputs
- Disadvantages:
 - Computationally intensive
 - The ease of application depends on the complexity of the model
 - There is no readily available software that facilitates application of Sobol's method

Example Application of Sobol's Method to the Simplified SHEDS Model

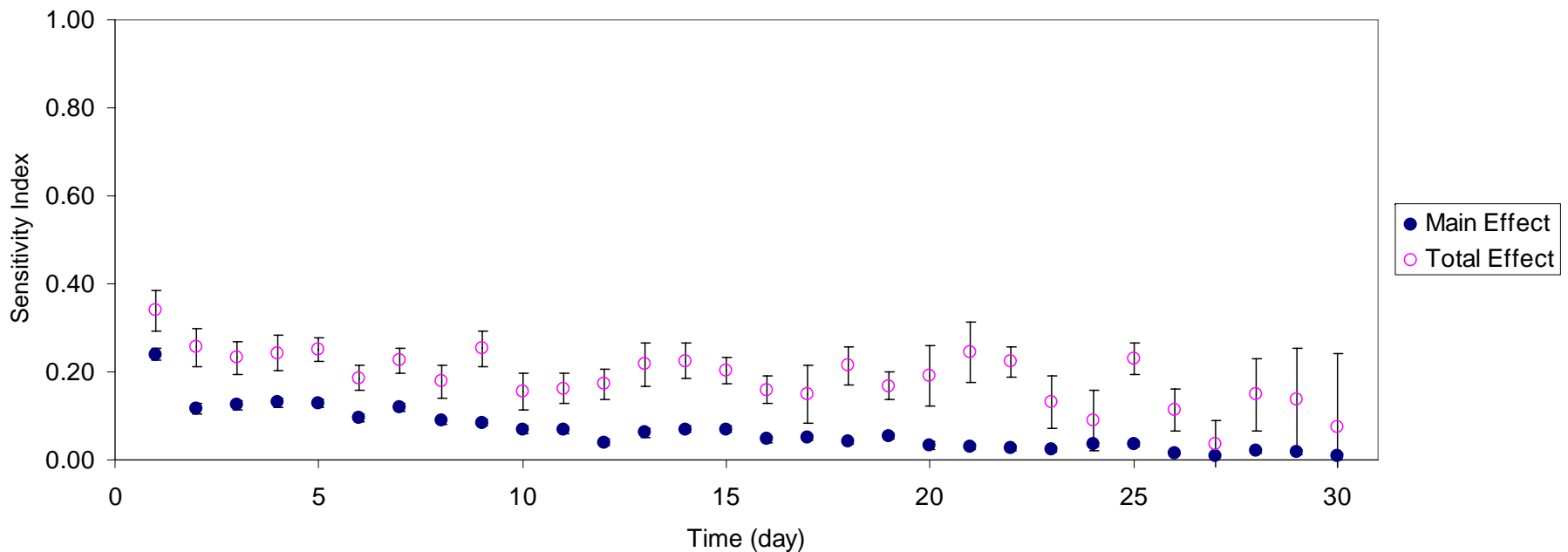
(a) Scenario I: Daily Exposure



Output: Inter-Individual Variability in Daily Exposure
Input: Residue decay rate (monthly)

Example Application of Sobol's Method to the Simplified SHEDS Model

(a) Scenario I: Daily Exposure

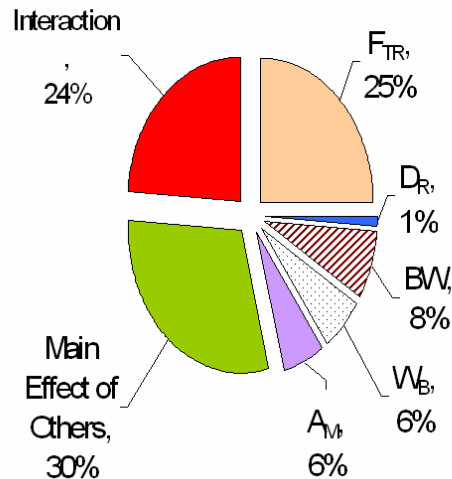


Output: Inter-Individual Variability in Daily Exposure

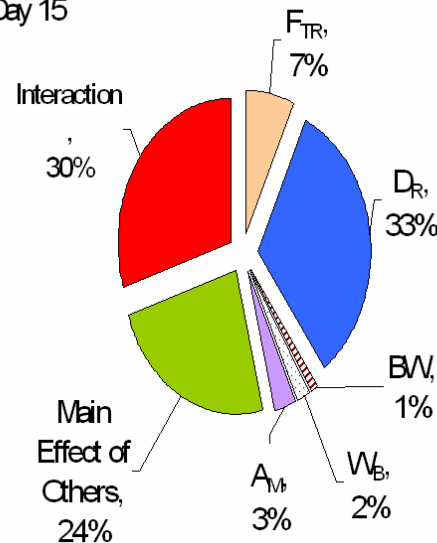
Input: Fraction of Chemicals Available for Transfer (Daily)

Contribution of Inputs to the Output Variance (Scenario I) Based on Sobol's Method

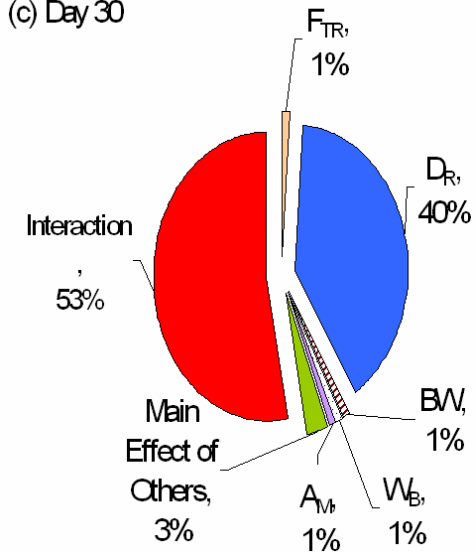
(a) Day 1



(b) Day 15



(c) Day 30



A_M = Mass of applied pesticide

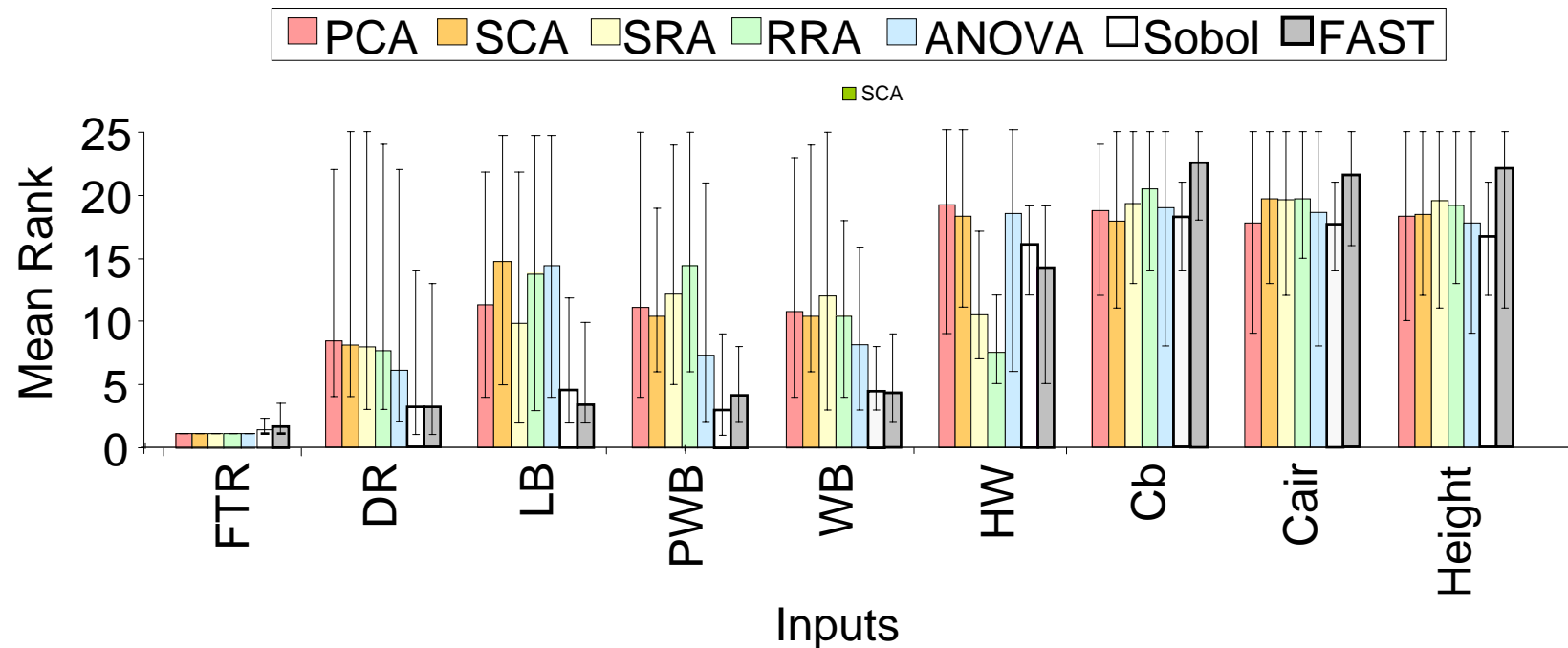
BW = Body washing removal efficiency

D_R = Fraction of pesticides that dissipates daily

F_{TR} = Fraction of pesticide available for transfer from surface to body or hands

W_B = Body weight

Quantitative Comparison of Sensitivity Analysis Methods for Selected Inputs



FTR = Fraction of chemicals available for transfer
DR = Fraction of residue that dissipates daily
LB = Maximum dermal load via body
PWB = Probability of washing body
WB = Body Weight

HW = Hand washing removal efficiency
Cb = Background air concentration
Cair = Concentration of applied pesticide in air
Height = Body height

Key Findings Based on Comparison of Selected Methods

- Variance-based methods provided lower mean ranks for the most sensitive inputs.
- The range of ranks for each input was typically narrower for the variance-based methods
- All methods provided similar results for insignificant inputs
- Sobol's method and FAST produced similar rankings, especially for important inputs.

Qualitative Comparison of Sensitivity Analysis Methods

	Sensitivity Analysis Method ^(a)						
Criteria for Comparison ^(b)	PCA	SCA	SRA	RRA	ANOVA	FAST	Sobol
Simultaneous Variation in Inputs	++	++	++	++	++	++	++
Computational Efficiency	++	++	++	++	+/-	-	-
Quantitative Measure for Ranking	++	++	++	++	++	++	++
Reproducibility	+/-	+/-	+/-	+/-	+/-	++	+/-
Ability to Apportion the Output Variance	No	No	+/-	+/-	+/-	++	++
Model Independence	No	No	No	No	Yes	Yes	Yes
Ability to deal with interactions	No	No	Yes	Yes	Yes	Yes	Yes
Robustness	+/-	+/-	+/-	+/-	+/-	++	++
Discrete Inputs	-	-	+/-	+/-	++	-	++
Number of Inputs	++	++	++	++	+/-	-	+/-

Conclusions

- Model independent methods are preferable
- Most methods can screen unimportant inputs
- Simple or convenient methods may fail to identify important inputs (e.g., because of interactions)
- Application to “2D” variability and uncertainty is possible (see food safety risk model case studies)
- Sensitivity differs at different time scales, which implies a need to match the time scale of the exposure analysis, sensitivity analysis, and assessment endpoint

Recommendations

- Sobol's method and FAST are attractive methods for apportioning the output variance.
- However, these are computationally intensive.
- Use a tiered approach:
 - a less computationally intensive and more readily available method can be applied for the purpose of determining which inputs are *not* important.
 - Unimportant inputs based on the tiered approach can be set to point estimates.
 - Subsequently, a more computationally intensive but also more accurate method, such as Sobol's method or FAST, can be applied to distinguish among the remaining inputs.

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- This report has not been subject to any EPA or Alion review. Therefore, it does not necessarily reflect the views of the Agency or Alion and no official endorsement should be inferred. The opinions, findings, and conclusions expressed represent those of the authors. Any mention of company or product names does not constitute an endorsement by the EPA or Alion.